Renewable and Sustainable Energy Reviews 16 (2012) 3370–3382

Contents lists available at SciVerse ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Grid integration of intermittent renewable energy sources using price-responsive plug-in electric vehicles

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ARTICLE INFO

Article history:
Received 11 July 2011
Accepted 5 February 2012
Available online 28 March 2012

Keywords:
Plug-in electric vehicles
Demand-side management
Variable prices
Intermittent generation

ABSTRACT

Plug-in electric vehicles (PEVs) are expected to balance the fluctuation of renewable energy sources (RES). To investigate the contribution of PEVs, the availability of mobile battery storage and the control mechanism for load management are crucial. This study therefore combined the following: a stochastic model to determine mobility behavior, an optimization model to minimize vehicle charging costs and an agent-based electricity market equilibrium model to estimate variable electricity prices. The variable electricity prices are calculated based on marginal generation costs. Hence, because of the merit order effect, the electricity prices provide incentives to consume electricity when the supply of renewable generation is high. Depending on the price signals and mobility behavior, PEVs calculate a cost minimizing charging schedule and therefore balance the fluctuation of RES. The analysis shows that it is possible to limit the peak load using the applied control mechanism. The contribution of PEVs to improving the integration of intermittent renewable power generation into the grid depends on the characteristic of the RES generation profile. For the German 2030 scenario used here, the negative residual load was reduced by 15–22% and the additional consumption of negative residual load was between 34 and 52%.

Contents

1. Introduction

Integrating high shares of fluctuating power generation into the electricity system requires flexible power plants, storage, power distribution via a reliable power grid and greater flexibility on the demand side. In terms of demand response [1] or the control of distributed load and generation units, we distinguish between direct control and indirect control. Direct control or centralized optimal charging implies that a service provider can shut down or reduce loads and control decentralized generation units directly. Examples include the direct load control of residential water heaters [2] and air conditioning loads in California, or of virtual power plants such as the "Dezentrales Energie Management System" (DEMS) of the German Siemens AG. The advantages of such direct control are prompt and predictable reactions to control signals. Drawbacks arise from reduced consumer acceptance in the case of controlling loads in private homes or vehicles and the

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doi:10.1016/j.rser.2012.02.019

communication and optimization efforts involved in controlling a large number of small storage or generation devices with varying consumer needs and providing mobility as primary purpose of use. Indirect control uses price signals to manage loads or generation units. In this case, the service provider sends price signals and the consumer (or an automatically controlled device programmed by the consumer) decides to either reduce or shift the load when the price is high, or pay the higher price. In this case, consumer acceptance should be higher than is the case for direct control [3]. Disadvantages arise from the possibility of avalanche effects or simultaneous reactions [4,5] and the necessity to predict the reaction of consumers to different price signals, which yields the possibility of forecasting errors. However, since consumer acceptance seems to be crucial for the feasibility of managing mobility-related systems, an indirect energy management system is considered the most promising option to control plug-in electric vehicles (PEVs). Hourly prices in combination with smart devices (devices such as thermostats or electric vehicles that optimize their demand depending on a control signal) are an adequate tool to involve consumers in the electricity markets [6,7]. The contribution of PEVs to improving the integration of intermittent renewable energy sources (RES) into the grid depends on technical issues such as storage capacity, grid connection power, and driving behavior, which together define the energy available for load shifting, as well as social and economic aspects which influence the incentive for consumers to participate in the load-shifting program. In this paper, we focus on modeling technical issues and driving behavior (see Section 2.3). Several recent studies discuss the impact of PEVs on power systems but do not consider the impact of RES on load shifting strategies [8–10], the dynamic mobility behavior and/or load shifting mechanisms [11–12].

For the analysis presented here, the agent-based electricity market equilibrium model PowerACE (see Section 2) is used to determine dynamic prices for a German 2030 scenario with a high share of intermittent generation (for the assumptions, see Section 3). The intermittency of the renewable generation affects the price signals (see Section 4) used for the distributed optimization of PEVs charging schedules. Hence, PEVs preferentially consume electricity when the supply of intermittent RES is high. Avalanche effects that can occur because of the similar optimization results of many devices are discussed in Section 5. In a case study for Germany, the effect of demand-side management with PEVs on the residual electricity load is evaluated and their contribution to integrating intermittent RES in the grid is shown (Section 6).

The present work is closely related to the Volkswagen and E.ON[1] field test “Flottenversuch Elektromobilität” funded by the German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (BMU). In the field test, price signals generated with the PowerACE model are sent to Volkswagen plug-in hybrid electric vehicles (PHEVs). Further, the same algorithms applied to optimize the charging behavior of the vehicles in dependence on price signals are also used in the simulation. In this way, consumer and real-life driving aspects will be able to be addressed in the future.

2. Simulation approach

The effects of PEVs on the electricity system are investigated using the market equilibrium model PowerACE in combination with indirect energy management and stochastic modeling of driving behavior. On the demand side, static and dynamic electricity demand as well as grid losses are considered on an hourly basis over one year of simulation. The dynamic demand is related to distributed devices that are able to optimize their market behavior, such as night storage heaters, electric vehicles or other shiftable loads.

On the supply side, RES, conventional power plants and storage technologies are considered. Details of the PowerACE model can be retrieved from [13] and an overview of the model is given in Fig. 1.

2.1. Demand-side management agent

Electric vehicles are implemented as part of a dynamic demand agent. The dynamic demand agent is structured in pools, groups and devices. A pool bundles several or at least one group and the group bundles several or at least one device.[2] In this study, a device represents a PEV. The group level is used for regionalization and grid restrictions. The device level represents all vehicle-specific information, including driving behavior and price-dependent optimization (see Section 2.2). Vehicle pools administer data for the groups and devices belonging to the specific pool. Each pool acts as an independent agent and can place demand and supply bids in the spot market. A pool adds up the expected operation $o_{d,g}$ of all the relevant devices in the different groups G. To keep the model as simple as possible, the operation o of a device d in group g is known at the pool level when the bid is placed in the spot market.[3] The operation O_p of pool p is calculated using Eq. (1):

$$O_p(t) = \sum_{d_{g1}=1}^{D_1} o_{d,g_1}(t) + \sum_{d_{g2}=1}^{D_2} o_{d,g_2}(t) + \sum_{d_{gn}=1}^{D_G} o_{d,G}(t) = \sum_{g=1}^{G}\sum_{d_g=1}^{D_g} o_{d_g,g}. \quad (1)$$

As a guidance signal for the devices participating in a pool, each pool performs a price forecast. The price forecast and the supply bids which result in the market clearing price are calculated according to the marginal costs. The marginal electricity costs c_{marginal} consist of the fuel price p_{fuel} to produce 1 MWh of electricity and the costs for the resulting CO_2 emissions. The CO_2 costs are given by the CO_2 coefficient, q_{CO_2}, which defines the CO_2 emitted when transforming a primary energy carrier, and the CO_2 price p_{CO_2}. Dividing the prices for fuel and CO_2 by the efficiency η of a specific power plant gives the marginal costs:

$$c_{\text{marginal}} = \frac{1}{\eta} * p_{\text{fuel}} + \frac{1}{\eta} * q_{CO_2} * p_{CO_2}. \quad (2)$$

To calculate the supply bid ($\text{bid}_{\text{supply}}$ price/capacity) of a power plant with a specific capacity, a markup factor m_{up} is added to the marginal costs:

$$\text{bid}_{\text{supply}} = \frac{c_{\text{marginal}} + m_{\text{up}}}{\text{Capacity}}. \quad (3)$$

The markup factor represents the margin or a markup to cover total costs. In the work presented here, base load power plants (on the left-hand side of the merit order in Fig. 2) in some cases place bids below the marginal costs to avoid start-up operations (negative markup), and peak power plants (on the right-hand side of the merit order in Fig. 2) place bids with positive markup to cover the full costs of the power plant. Because of the very low costs of operation for intermittent RES, marginal electricity costs of zero are assumed. Hence, RES supply with priority and reduce the power required from controllable power plants (Section 4).

The 2030 market clearing prices (PowerACE) for one year (8760 h) and the merit order of all power plants available in the 2030 scenario (see Section 3) are shown in Fig. 2. The figure also

[1] E.ON is utility enterprise.

[2] The structure was selected to model a general demand-side management agent which could not only include PEVs but also devices with thermal storage such as heat pumps and freezers or DSM devices without storage. Here, only PEVs are included.

[3] The pool places a price-independent bid. Hence, the bid must be always cleared.

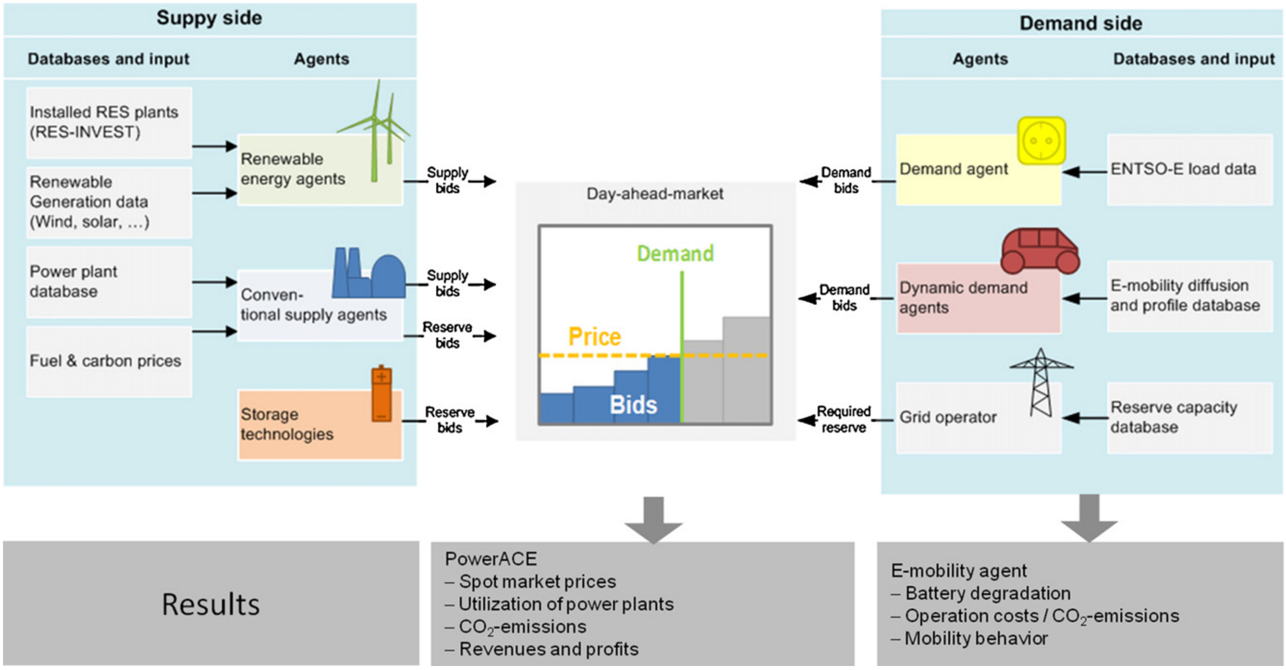

Fig. 1. Structure of the PowerACE model.

Source: Fraunhofer ISI.

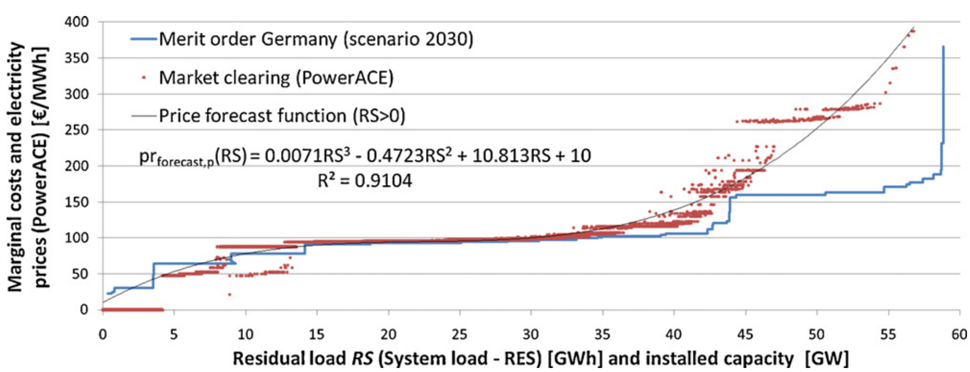

Fig. 2. Merit order and clearing price bids in a German 2030 scenario. Simulated with the PowerACE model; fuel and CO_2 prices according to [19] Scenario A "deutlich"; installed convention generation capacities based on own estimations. Installed capacity: oil 0.7 GW; gas turbines 16.4 GW; combined gas and steam 10.2 (η = 45–59%) and 25.6 GW (η = 60–65%); coal 8.7 GW, lignite 9.2 GW; waste 0.9 GW.

gives a price forecast function of the marginal electricity costs over the residual load (RS) which is used to determine the forecast price of a pool. To calculate the residual load RS (Eq. (4)), perfect foresight for the inelastic electricity demand $D_{\text{Inelastic}}$, the exchange balance Ex and the generation of renewable energy sources RES are used:

$$\text{RS}_p(t) = D_{\text{Inelastic}}(t) + \text{Ex}(t) + O_P(t) - \text{RES}(t). \tag{4}$$

The expected operation of all pools O_P is calculated individually for each pool one after the other according to Eq. (5):

$$O_{P,p}(t) = \frac{P}{p-1}\sum_{n=1}^{p-1} O_n(t). \tag{5}$$

The operation of the pools in which devices have already optimized their demand (pool p) is known and scaled up to estimate the operation of all pools. Using the residual load, the pool performs a two-day forecast for the expected prices $\text{pr}_{\text{forecast}}$ using Eq. (6):

$$\text{pr}_{\text{forecast},p}(\text{RS}) = 0.0071 \cdot \text{RS}^3 - 0.4723 \cdot \text{RS}^2 + 10.813 \cdot \text{RS} + 10 \tag{6}$$

for RS values greater than zero. For a RS equal zero or negative a linear correlation[4] is used.

The assumption that the generation of intermittent RES and the elastic demand is known is obviously not realistic for an actual electricity market. This method is used because the focus of this analysis is the indirect control of PEVs and their ability to integrate intermittent RES. A study discussing possible market organizations is presented in [14].

2.2. Vehicle-based optimization of the load profile

The used simulation structure[5] considers the superior market situation represented by the pool level and the local distribution network situation represented by the group level. Devices are affected by both levels due to different tariff components.

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[4] pr = RS + 10.

[5] Simulation structure, a pool contains groups and a group contains devices or PEVs, respectively.

At the group level, a variable grid fee is added to the price component of the pool level to avoid overloading in the distributed network (see Section 5). Therefore, a simple quadratic relation between the variable grid fee $pr_{gridfee,g}$ and transformer utilization $u_{Transformer,g}$ is used:

$$pr_{gridfee,g}(t) = a * u^2_{Transformer,g} + c. \tag{7}$$

The constant parameters a and c are selected, such that the total grid fee is constant for one day at a transformer. Hence, the sum of the constant grid fee multiplied by the power at the transformer for all time steps t of a respective day is the same as using the variable grid fee assuming that the vehicles charge after their last journey of the day.

The transformer utilization is calculated by dividing the power at the transformer in time step t by the nominal transformer power $W_{Transformer}$. The power at the transformer is calculated by adding the standard load profile $W(t)$ for Germany [15] and the operation $o_{d,g}(t)$ of the PEVs already processed:

$$u_{Transformer,g}(t) = \frac{W(t) + \sum_{n=1}^{(d-1)} o_{d,g}(t)}{W_{Transformer}}. \tag{8}$$

After each optimization of a device, the operation $o_{d,g}(t)$ of the PEVs is known and the expected utilization of the transformer changes. As for the pool price forecast, this is a theoretical approach to avoid avalanche effects (see Section 5). Today, equal treatment of electricity consumers is required and therefore customer-specific tariffs are not allowed in Germany.

The resolution of the grid price and the operation of PEVs at grid level are 15 min blocks of time or 96 time steps per day. The devices optimize their operation depending on a price signal to minimize costs. The price for a specific device pr_d comprises the pool forecast price $pr_{forecast,p}$ (see Eq. (9)), the variable grid fee $p_{gridfee,g}$ and the sales tax r_{tax}:

$$pr_d(t) = (pr_{forecast,p}(t) + pr_{gridfee,g}(t)) \times (1 + r_{tax}). \tag{9}$$

The sales tax used do not influence the results in the simulation. This value is implemented because the calculated tariff is also used in a field test [16] and the optimization is done from a consumer point of view. In this case, the sales tax widens the price spread and therefore increases the consumer incentives.

The local optimization uses a graph search algorithm to minimize the charging costs [17]. The algorithm calculates a schedule for charging and discharging the vehicle battery in the optimization time period. The algorithm is applied when the vehicles are plugged into the grid after each trip. In addition to the price pr_d, the usable battery capacity, the state of charge (SOC), the beginning and end of the optimization, the grid connection power and battery degradation all enter the schedule calculation. After a new optimization, the previous schedule is invalid. A detailed description of the applied algorithm is given in [18].

The optimization time period depends on the SOC when returning to the grid and follows the values in Table 1.

2.3. Driving behavior

A stochastic approach is used to estimate driving behavior. The data is taken from the travel survey "Mobility in Germany" [19]. In order to find user segments that are suitable for electric driving, the raw data is filtered [20]. Early adopters of PEVs can be characterized by a high annual driving mileage due to economic reasons. Compared to conventional vehicles the investments in PEVs are higher but the operating costs are lower. We consider technical aspects as well as economic aspects. Possible PHEV and BEV users are required to have an assigned parking space. Additional requirements for BEVs include the availability of more than one vehicle per household and regular job-related trips shorter than 90 km.

Modeling driving behavior can be simplified to three probability parameters which are defined as follows.

The probability to travel with the vehicle on a certain day Pro_{travel} (day):

$$Pro_{travel}(\text{day}) = \frac{1}{m_{day}} \times \sum_{i=1}^{m_{day}} Travel_i(\text{day}). \tag{10}$$

where $Travel_{day}$ is a Boolean value (true, false) indicating whether the respondent is driving on day and m_{day} represents the sample size on a given day of the week. We found distinct patterns of traveling behavior on Sun, Sat, Mon, Fri and other weekdays. Weekdays are defined as Tuesday, Wednesday and Thursday and merged into one data set because the driving behavior on these days was found to be very similar.

The probability for starting a trip Pro_{start} on a specific day and time slot is given by:

$$Pro_{start}(\text{day}, t) = \frac{1}{n_{day}} \times \sum_{n=1}^{n_{day}} n(\text{day}, t). \tag{11}$$

n_{day} represents all samples with a trip on a specific day and n(day, t) a trip started at a specific time t. t is a parameter out of 0–95, or a 15 min time resolution during a day, respectively. The average trips[1] per day, while Pro_{travel} = true are multiplied with $Prob_{start}$ to account for multiple trips per day.[6]

Range and duration are correlated. The different range values are classified in $k := \{0, \ldots, 20\}$. The probability Pro_{range} at a specific day for a range class k is:

$$Pro_{range}(\text{day}, \text{range} \in k) = \frac{1}{n_{day}} \times \sum_{i=1}^{n_{day}} n(\text{day}, k). \tag{12}$$

The class specification is given in Table 8 in Appendix A.

For the data used, a linear correlation was found between range r and duration du, which is shown in Fig. 3.

The duration du(r) is given in Eq. (13):

$$du(r) = 0.6837r + 5. \quad R^2 = 0.92 \tag{13}$$

Including aspects related to the infrastructure in the simulation model requires an additional probability value:

$$Pro_{loc}(\text{day}, t, \text{location} \in k) = \frac{1}{n_{day}} \times \sum_{n=1}^{n_{day}} n(\text{day}, t, k). \tag{14}$$

$Pro_{location}$ represents the probability trip ending at k out of 0 ... 4 locations. In the work presented here, infrastructure is not considered. We assume that PEVs are plugged-in after each travel trip and that the necessary infrastructure is available.

3. Assumptions

In order to analyze the effect of fluctuating renewable energy generation from wind power and photovoltaic, as well as the contribution of PEVs towards balancing this RES, we constructed a scenario for 2030. The hourly characteristic of the demand in Germany is taken from [21]. For 2030, a yearly demand of 502.1 TWh is assumed [22]. To indicate the supply side, the merit order of power plants is generated using primary energy and CO_2 prices from [23, Scenario A "deutlich"]. Based on the current German power plant mix, all power plants reaching the end of their life cycle life by 2030 are assumed to be replaced by gas turbine power stations and combined-cycle plants. The capacity of intermittent renewable energy sources (RES) for the 2030 scenario is taken from

[6] Average trips per day Mon = 3.950, Weekday = 3.965, Fri = 4.211, Sat = 5.597, Sun = 2.810.

Table 1
Optimization time to recharge the battery storage.

Optimization	State of charge (SOC)	SOC < 0.3	SOC < 0.7	SOC ≥ 0.7	Unit (1 = 15 min)
After a trip	Storage < 5 kWh	8	32	60	Time steps
	Storage ≥ 5 kWh	16	56	60	Time steps
Every day at 22 o' clock	–	38	38	38	Time steps

Table 2
Used structure of pools, groups and devices[a].

Pool	Group	Dev1 PHEV27	Dev2 PHEH57	Dev3 City-BEV	Dev4 BEV	Sum	Grid power	Total storage	Transformer capacity
		[1000 units]					[GW]	[GWh]	[kVA]
1	1	129	220	41	10	400	1.80	4.14	4 kVA/Dev + Household
1	2	130	219	41	10	400	1.80	4.13	4 kVA/Dev + Household
...									
1–9	Sum	2331	3951	738	180	7200	32.47	74.37	–
10	1	259	439	82	20	800	3.61	8.26	4 kVA/2× Dev + Houshold
...									
10–15	Sum	1554	2634	492	132	4812	21.74	49.94	–
1–15	Sum	3885	6585	1230	300	12,000	54.12	123.95	–

[a] *Source*: Dominanz-Szenario [20].

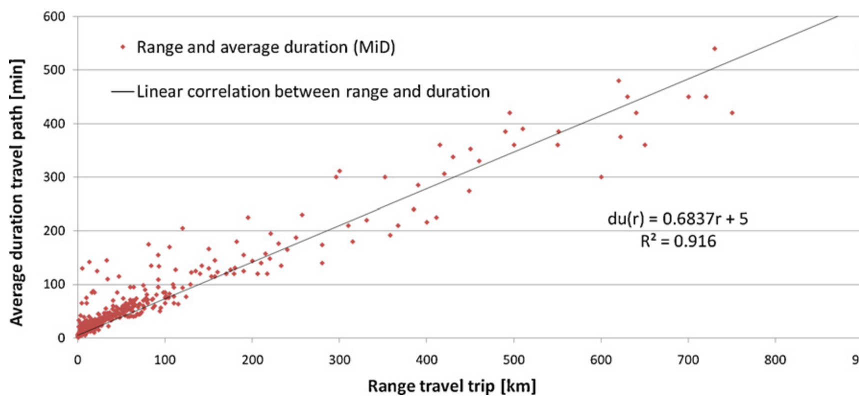

Fig. 3. Correlation between the average duration of a trip and the range of a trip. The used data is filtered according to [20] and uses raw data from [19].

[23,Scenario A]. The installed capacity of onshore wind, offshore wind and photovoltaic is 37.8 GW, 25 GW and 63 GW, respectively. The hourly characteristic of intermittent renewable energy sources for electricity production is taken from [21] for wind onshore and [24] for wind offshore and photovoltaic. The imports and exports of electricity and storage technologies like hydro pump storage are not taken into account.

The demand of BEVs and PHEVs is modeled (see Section 2) using the probabilities describing the driving behavior of the mobility survey MiD 2002, which was aggregated according to [20]. The probabilities used are available in Appendix A.

The penetration of PEVs is taken from [25]. In the 2030 scenario, 12 million PEVs will be on the roads in Germany. Table 2 shows the allocation of the PEVs in vehicle pools. The pools 1–9 are composed of two groups and pools 10–15 are composed of one group which results in a different transformer capacity available per vehicle. In this model, the operation of the vehicles is scaled-up by a factor of 1000. In total, 12 thousand PEVs are modeled, representing 12 million PEVs.

The different PEV types used are shown in Table 3. The values represent an average of the specific vehicles.

In the quadratic equation to estimate the grid-related price component (see Section 2.2), a is assumed to be 30 and c is 0.5.

Table 3
Assumptions for the different types of plug-in electric vehicles (PEVs).

Dev	Type	Storage usable energy [kWh]	Grid connection power [kW]	Equivalent energy use [kWh/km]
1	PHEV(25)	4.5	4	0.18
2	PHEV(57)	12	4	0.21
3	City-BEV(100)	15	8	0.15
4	BEV(167)	30	8	0.18

PHEV: plug-in hybrid electric vehicle and BEV: battery electric vehicle. Value in brakes is the theoretical driving range in km

4. Characterization of the merit order effect

An important aim of the work currently being conducted is to investigate how PEVs can be used to improve the integration of intermittent RES and balance the fluctuation of these power sources, mainly wind power and photovoltaic. The effect of intermittent RES on electricity prices, known as the merit order effect, plays an important part in the applied approach [26]. The indirect control of PEVs uses a tariff that depends on marginal electricity costs and therefore on the residual load.

Fig. 4 shows the merit order of the power plants available in Germany in 2008 (left curve in Fig. 4). Taking the same marginal costs and power plants, but including the installed capacity of wind power and photovoltaic shifts the merit order to the right (right curve in Fig. 4). It is unlikely that the total installed capacity of intermittent RES is available simultaneously, but it can be concluded that these intermittent RES do reduce the marginal costs and therefore the clearing prices in the electricity market at least to some extent [27].

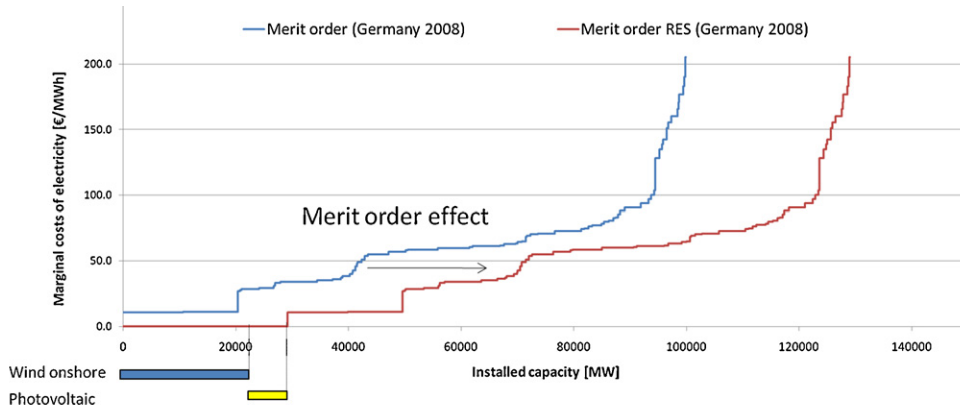

Fig. 4. Merit order of the power plants in Germany 2008 with and without the installed capacity of wind and photovoltaic.
Source: own calculation using data from [23] for the installed capacity of wind and photovoltaic.

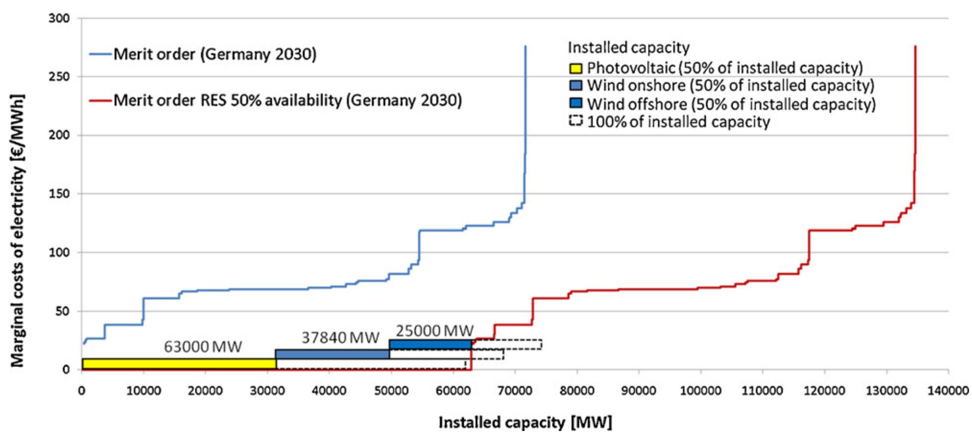

Fig. 5. Merit order of the power plants in a 2030 scenario for Germany with and without 50% of the installed capacity of wind and photovoltaic.
Source: own calculation using data from [23] for the installed capacity of wind and photovoltaic.

For the 2030 scenario (see Section 3), the effect on the merit order due to photovoltaic and wind generation increases (see Fig. 5). We assume a situation in which energy generated from photovoltaic and wind makes up 50% of the installed capacity. This situation will result in marginal costs of zero for 60 GWh demand.[7] If no intermittent RES supply is available in this demand situation, the marginal costs would be 120 € per MWh.

This example shows how intermittent RES affect the marginal costs of electricity and that future electricity markets will have more volatile prices. It is very likely that higher shares of intermittent RES will also increase the base peak spread of electricity prices. This is because of an expected increase in fuel and CO_2 prices and a tendency for bids to include a higher markup factor to cover the full costs of conventional power plants.

5. Avalanche effects

Indirect control of distributed generation and flexible loads with variable tariffs has one major drawback. If an automated optimization of devices is used, a price signal which is valid for all devices can cause demand or generation peaks, known as avalanche effects [4,5,28]. These effects are induced by an optimum to consume or feed-back electricity in one specific time period which has the lowest or highest prices for electricity. Assuming that all devices have the same degree of freedom (actual and favored state of charge at the end of the optimization time, grid connection time, and so on) in a specific time period for load-shifting or generation will reinforce this effect. In the case of electric vehicles, however, the degree of freedom is affected by driving behavior and the willingness of the users to shift loads and to plug-in the vehicle.[8]

Fig. 6 shows the optimization result of PEVs for three PEV pools using the same price forecast (no grid fee is assumed). Driving behavior affects the amount of energy required to recharge the battery and the time steps in which the PEVs are connected to the grid. The demand of all PEVs collected in the pools 1–3 is very similar. Only pool 1 shows slightly different results. The diffusion of the demand results from the limited grid connection power[9] and differences in driving behavior.

Using individual price forecasts for the different pools results in a greater diffusion of the PEV pool demand (see Fig. 7).[10]

The avalanche effects are reduced and PEV demand is better distributed to fill load valleys (see Fig. 9 in Section 6). In real electricity markets better allocation is achieved using price elastic demand bids.[11]

[7] The German simultaneous hourly annual peak load in 2008 was 76.8 GW.

[8] The willingness of the consumer to react to incentives is not part of this paper. We excluded this aspect in order to examine the effects of PEVs without the necessary assumptions about consumer incentives.

[9] If it is not possible to completely recharge the battery in the time step with the lowest price, the next time step is used.

[10] Perfect forecast is assumed. Hence the reaction of other pools is known (feedback) and/or estimated (see Section 2).

[11] [10] shows that a Nash equilibrium in case of PEVs is possible.

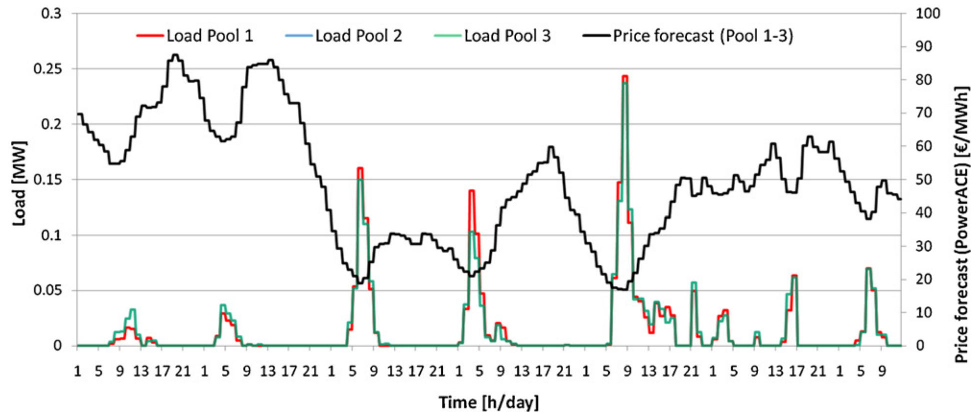

Fig. 6. Demand of three PEV pools with the same price signal.

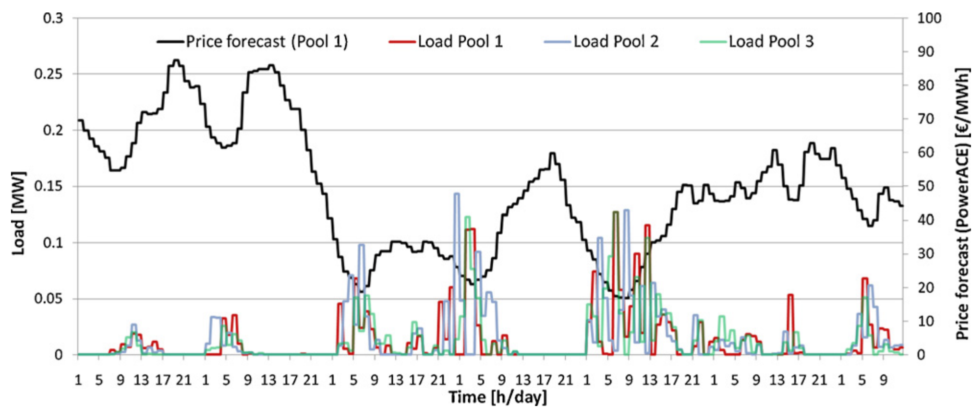

Fig. 7. Demand of three PEV pools with different price forecast.

Avoiding peaks in the total system load can still result in load peaks in distribution electricity networks. A strong increase in wind generation, for example, can necessitate the concentration of additional demand within a short time period. At the group or distribution network level, therefore, a variable grid fee is used to guarantee that the transformer is not overloaded. This variable grid fee is specific to each device (see Section 2). Due to the assumed perfect demand forecast of other devices and electricity users within the distribution network, the grid fee increases after each demand optimization of a device (feedback loop). Hence, the optimal loading time period shifts and the utilization of the transformer is evened out. Depending on the situation at the system level and in the local network, price components at the pool and the group level can provide incentives for the same time periods or counteract each other.

Fig. 8 shows transformer utilization with and without PEVs for one group (we assume that a 400 kVA transformer hosts 100 households and 100 PEVs). The function of the dynamic grid fee over the transformer utilization is also shown.

Transformer utilization is not critical with the variable grid fee used for the 2030 scenario. An increase from about 25% to 35% on 15 min basis can be observed.

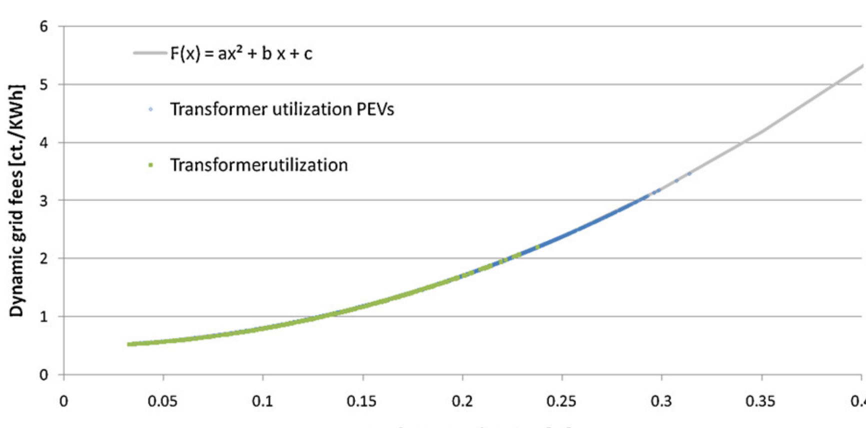

Fig. 8. Transformer utilization with and without plug-in electric vehicles (PEVs) and the function between the dynamic grid fee and transformer utilization.

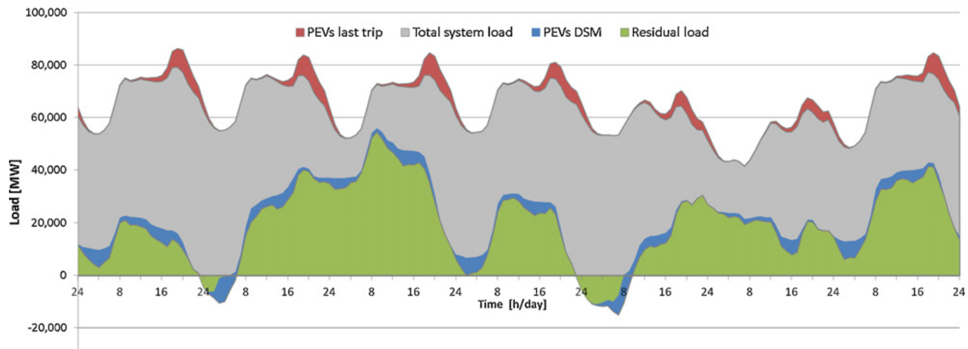

Fig. 9. Load of plug-in electric vehicles (PEVs) charging after the last trip and using demand-side management (DSM). First three weeks of the year 2030 scenario. Renewable energy fluctuation based on the weather year 2008 [24].

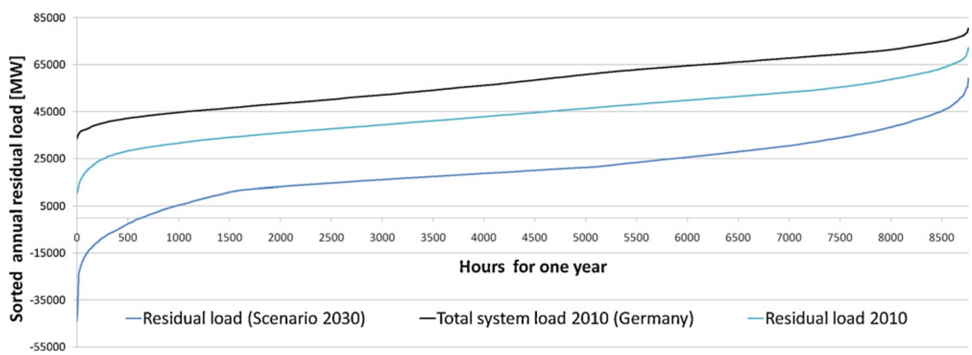

Fig. 10. Sorted total system load and sorted residual load 2010 as well as sorted residual load 2030. See Section 3 for the assumptions.

6. Results

The model results based on the assumptions outlined in Section 3 are presented in the following section. Unlike other publications (e.g. [8,9]), the PEVs' load follows the residual system load and does not simply shift demand to the night-time hours (see Fig. 9). The intermittency of renewable energies makes it necessary to take this advanced view of base and peak load. Further, the load shifting follows a dynamic pricing approach with a distributed vehicle-based optimization which considers mobility behavior, local grid restrictions and consumer incentives.

Comparing the demand-side management (DSM) with simple charging after the last trip in Fig. 9 shows a reduced peak load. PEVs preferentially consume energy when the residual load is low or even negative.

In the assumed scenario, the installed capacity of wind and photovoltaic rises from 46 GW in 2010 to 125 GW in 2030 (see [23], pp. 186–187). Comparing the residual load in 2010 with the residual load in the 2030 scenario (see Fig. 10) illustrates the switch to electricity systems with higher shares of intermittent generation from renewable energy sources.[12] For 2030, we expect 635 h with a negative residual load (in total 5.36 TWh), which means that the generation of intermittent photovoltaic and wind power plants is higher than the assumed demand. The minimum of the residual load drops from 10.4 GW in 2010 to −43.7 GW in 2030.

In order to analyze the PEVs' contribution towards improving the integration of intermittent RES, we focus on three key values: the change in the minimum residual load, the percentage of negative residual load that can be consumed using load shifting, and the residual load change ($RS_{(t)} - RS_{(t-1)}$). The characteristic of the RES intermittency and the energy produced influences the PEVs' ability to balance RES. To account for this we analyze different weather years with specific wind on- and offshore as well as photovoltaic data for 2006–2008 [21,24]. To compare the different RES characteristics, we additionally scale the 2006 and 2007 data to the RES energy production (325 TWh) in 2008 (see Tables 4 and 5 "scaling").

Fig. 11 shows the effect of PEVs on the residual load for the two charging scenarios with weather characteristics for 2008. Compared to uncontrolled charging after the last trip, demand-side management (DSM) can prevent an increase in the peak load (for all the weather years analyzed).

The minimum of the negative residual load is reduced by 8.0 GW to −35.7 GW in the case of DSM (see Fig. 12). 2.82 TWh or 52.6% of the negative residual load can be consumed using load shifting.

Considering the different weather years in Table 4 shows a peak reduction in the negative residual load of between 15 and 22% or about 6–8 GW. The negative residual load usable with DSM (=(neg. RS − neg. RS DSM)/neg. RS) varies between 34 and 52%. This corresponds to 14.3% (2.56 TWh) and 20.4% (3.66 TWh), respectively, of the 17.9 TWh consumed in total by the PEV fleet.

This shows that the characteristic of intermittent RES strongly influences minimum peak reduction and negative RS able to be used by DSM. A more balanced RES generation with a higher availability on each day of the year (e.g. offshore wind) or short recurring photovoltaic generation peaks are better able to be used than extreme weather conditions with particularly strong or no wind periods. That is because, in the case of DSM, only the electricity used for driving (on average 49 GWh per day) can be used for load shifting.

[12] In the simulation presented here we did not consider pumped storage or trans-border flows.

Table 4
Results of the negative residual load (RS) peak reduction and usable negative residual load with different renewable energy intermittency.

	Unit	2006	2006 scaling	2007	2007 scaling	2008
RES generation	TWh	306.97	325.20	336.87	325.20	325.10
Min. RS power	GW	−37.19	−43.99	−40.75	−37.35	−43.74
Min. RS power DSM	GW	−30.72	−37.05	−32.01	−28.90	−35.74
Min. RS reduction DSM		17.42%	15.78%	21.45%	22.61%	18.29%
Negativ RS	TWh	−6.16	−9.87	−9.25	−6.83	−5.36
Negativ RS DSM	TWh	−3.60	−6.44	−5.59	−3.89	−2.54
Negative RS usable DSM		41.55%	34.77%	39.61%	43.09%	52.58%

Table 5
Results of the residual load (RS) change versus RS change including plug-in electric vehicles (PEVs) using demand-side management (DSM) with different renewable energy intermittency.

	Unit	2006	2006 scaling	2007	2007 scaling	2008
Residual load (RS)						
Load change Min.	GW	−15.39	−16.16	−14.64	−14.15	−14.41
Load change Max.	GW	18.88	19.77	16.33	15.82	22.13
RS + PEVs (DSM)						
Load change Min.	GW	−15.71	−16.76	−12.88	−11.98	−14.45
Load change Max.	GW	18.73	19.60	16.05	15.77	17.90

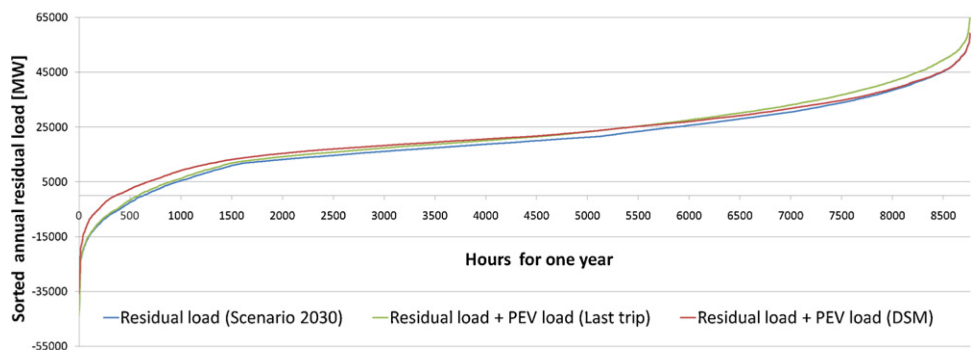

Fig. 11. Effect of plug-in hybrid electric vehicles (PHEVs) on the residual load when charging after the last trip and using demand-side management (DSM). See Section 3 for the assumptions.

In general, mobility behavior restricts load shifting capability, so PEVs are suitable for short-time storage (1–2 days).

The hourly load change of the residual load with and without price-controlled PEVs is shown in Fig. 13. The effect of different weather years on the residual load change is relatively small (represented by the width of the lines in Fig. 13). Further, for the RES generation and load curve considered, the average positive delta ($RS_{(t)} > RS_{(t-1)}$ on the right side of Fig. 13) is higher than the average negative delta ($RS_{(t)} < RS_{(t-1)}$ on the left side of Fig. 13). As a result, a rapid generation increase is required more often to balance the system. Price-controlled PEVs can reduce the load change from one hour to the next in both cases. For the extreme values, the variation between different weather years is high (see Table 5).

For the 2008 weather data, the highest ramp down is −14.41 GW versus −14.45 GW using controlled PEVs and the highest ramp up is 22.13 GW versus 17.90 GW. For the extreme ramp down value the used load management mechanism does not necessarily result in system benefits (see Table 5).

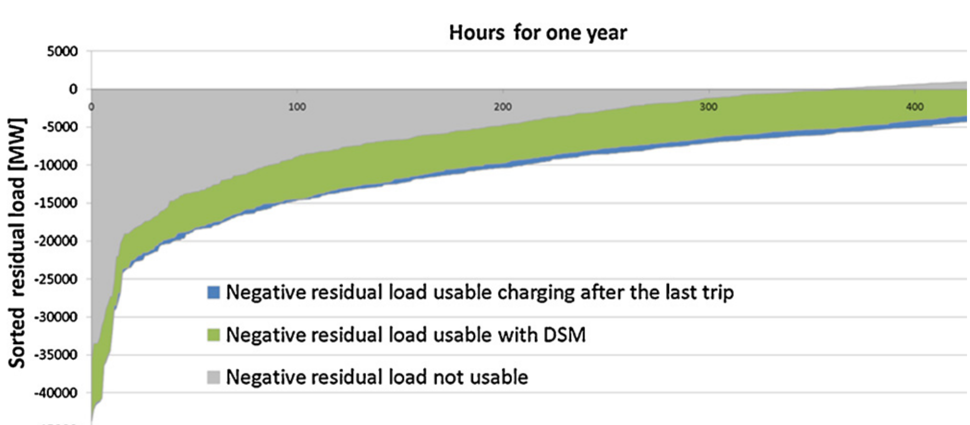

Fig. 12. Detail screen of the negative residual load when charging after the last trip and using demand-side management (DSM).

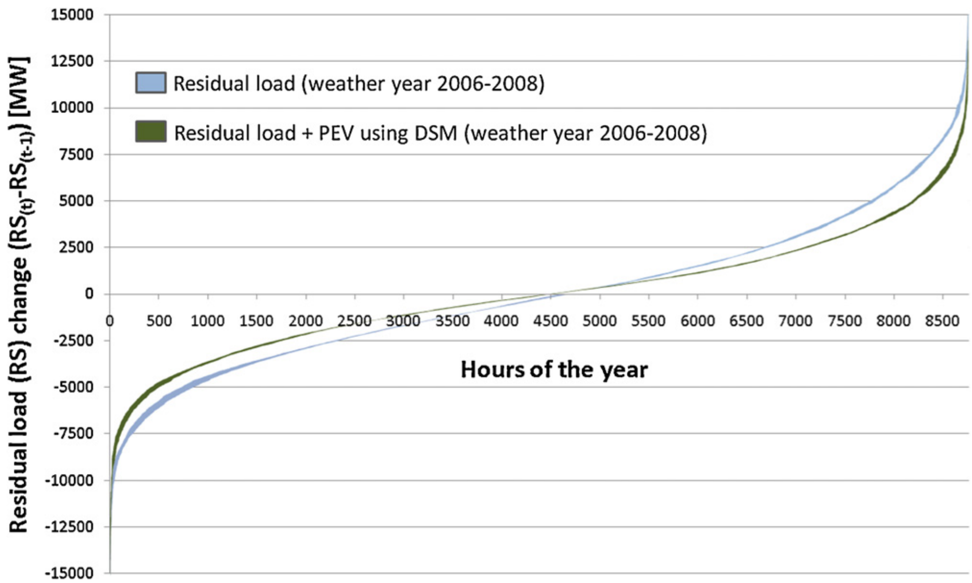

Fig. 13. Sorted hourly load change of the residual load versus the residual load change using demand-side management (DSM) with plug-in electric vehicles.

7. Conclusions

In the presented paper, we investigated the capability of plug-in electric vehicles (PEVs) to balance intermittent renewable energy sources (RES) in a 2030 case study for Germany. The conclusions in detail are:

PEVs provide a very high power/energy ratio: Compared with other storage devices, PEVs are able to offer a high total connection power. A fleet of PEVs provide power totalling 54.12 GW (2030 scenario with 12 million PEVs) with a relatively low usable amount of battery storage of 123.95 GWh (ratio 0.44). By comparison, German pumped-storage plants provide 7.76 GW with a rated volume of 224.31 GWh (ratio 0.035).

Driving behavior restricts the use of mobile storage: The main purpose of PEVs is to fulfill mobility needs at equivalent costs to those of conventional vehicles. A cost-sensitive consumer will maximize the distance driven electrically in order to recoup the higher initial investment. This implies high utilization of the battery and therefore reduces the time period available for load shifting and/or vehicle-to-grid services. PEVs are therefore utilizable as a short-time storage option (1–2 days) with limitations (e.g. infrastructure or consumer needs) on the load management time during the day.

Price-based load shifting mechanisms require a feedback loop: The load management mechanism presented uses dynamic prices as a control signal for PEVs and takes the effect of intermittent renewable energy sources, mobility behavior as well as local grid restrictions into account. To avoid avalanche effects of automated control a feedback of transformer utilization is included. This implies that PEVs have access to information about the reaction of other PEVs in the same distribution network. In practice, this could be realized in the form of distributed grid monitoring carried out by PEVs and/or the presented dynamic grid fee. Such a system does not yet exist but seems to be technically feasible.

The consumer reaction on price signals is unclear: The economic incentives from electricity markets are low. The current base peak spread at the European Energy Exchange (EEX) is only about 3 ct./kWh. In the presented approach, we assumed an infinite price elasticity of the consumer. Consequently, the PEVs' load is able to be shifted to different time periods even in the case of very low incentives. Real consumer reaction in the case of the used load management mechanism is unclear.

PEVs can contribute to balancing intermittent RES: To analyze PEVs' contribution to balancing intermittent RES, three evaluation parameters were defined: the change in the minimum residual load, the percentage of negative residual load that can be consumed using load shifting, and the residual load change. For all three aspects, PEVs make a positive contribution to improving the integration of intermittent RES into the electricity system.

The characteristic of RES intermittency greatly influences the results: The results are influenced by the generation share and the profile of intermittent RES, e.g. wind or photovoltaic. Especially for the percentage of negative residual load that can be consumed we found high variation depending on the RES characteristic. The expected higher utilization of power from German offshore wind parks during night-time hours supports the positive contribution of PEVs to integrating intermittent RES. The amount of power generated by wind turbines obviously depends on local climatic conditions and varies from country to country. Therefore, the presented results are only valid for a German 2030 case study and the calculated values cannot be universally applied.

Acknowledgements

This work has been co-financed under grant of the German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (BMU) as part of the project "Flottenversuch Elektromobilität". We thank Ilan Momber, Patrick Plötz, Fabian Kley and Gillian Bowman-Köhler for discussions and critical reading of the manuscript.

Appendix A. Appendix

See Tables 6–8.

Table 6
Probability of travel.

Mon	Weekdays	Fri	Sat	Sun
62.73%	65.86%	64.94%	54.99%	40.66%

Table 7
Probability for starting a trip (sliding average).

Time	Mon	Weekdays	Fri	Sat	Sun
0	0.04%	0.06%	0.09%	0.17%	0.08%
1	0.03%	0.03%	0.07%	0.14%	0.05%
2	0.03%	0.04%	0.13%	0.17%	0.07%
3	0.02%	0.03%	0.12%	0.12%	0.04%
4	0.02%	0.03%	0.12%	0.12%	0.04%
5	0.00%	0.03%	0.09%	0.07%	0.03%
6	0.00%	0.03%	0.09%	0.06%	0.03%
7	0.00%	0.03%	0.03%	0.04%	0.02%
8	0.03%	0.03%	0.04%	0.08%	0.02%
9	0.03%	0.02%	0.03%	0.08%	0.01%
10	0.03%	0.02%	0.05%	0.07%	0.05%
11	0.03%	0.02%	0.03%	0.06%	0.05%
12	0.03%	0.03%	0.05%	0.07%	0.11%
13	0.01%	0.03%	0.03%	0.03%	0.10%
14	0.02%	0.03%	0.09%	0.05%	0.12%
15	0.02%	0.03%	0.12%	0.05%	0.08%
16	0.02%	0.04%	0.13%	0.05%	0.08%
17	0.04%	0.06%	0.12%	0.03%	0.03%
18	0.10%	0.15%	0.17%	0.02%	0.09%
19	0.14%	0.18%	0.18%	0.04%	0.10%
20	0.28%	0.30%	0.28%	0.08%	0.14%
21	0.33%	0.36%	0.35%	0.11%	0.14%
22	0.56%	0.53%	0.50%	0.19%	0.15%
23	0.64%	0.59%	0.58%	0.21%	0.14%
24	0.91%	0.88%	0.76%	0.25%	0.13%
25	1.11%	1.03%	0.95%	0.30%	0.13%
26	1.39%	1.40%	1.21%	0.39%	0.18%
27	1.53%	1.54%	1.29%	0.37%	0.19%
28	1.79%	1.97%	1.63%	0.49%	0.28%
29	1.77%	1.93%	1.67%	0.57%	0.37%
30	1.80%	2.02%	1.70%	0.78%	0.54%
31	1.65%	1.77%	1.57%	0.90%	0.63%
32	1.55%	1.78%	1.71%	1.31%	0.83%
33	1.42%	1.46%	1.50%	1.42%	0.94%
34	1.60%	1.57%	1.59%	2.07%	1.25%
35	1.46%	1.41%	1.39%	2.10%	1.32%
36	1.70%	1.52%	1.59%	2.69%	1.60%
37	1.59%	1.38%	1.41%	2.54%	1.64%
38	1.76%	1.53%	1.57%	3.27%	1.88%
39	1.52%	1.30%	1.48%	2.93%	1.68%
40	1.64%	1.41%	1.66%	3.24%	1.75%
41	1.37%	1.30%	1.47%	2.81%	1.52%
42	1.65%	1.53%	1.63%	3.25%	1.90%
43	1.38%	1.31%	1.43%	2.70%	1.69%
44	1.49%	1.45%	1.50%	2.76%	2.09%
45	1.29%	1.37%	1.31%	2.43%	2.08%
46	1.57%	1.68%	1.49%	2.76%	2.61%
47	1.33%	1.53%	1.41%	2.34%	2.19%
48	1.57%	1.71%	1.64%	2.51%	2.15%
49	1.43%	1.60%	1.45%	2.20%	1.78%
50	1.65%	1.79%	1.79%	2.46%	2.20%
51	1.43%	1.49%	1.68%	1.93%	1.68%
52	1.58%	1.53%	1.71%	2.07%	1.90%
53	1.37%	1.34%	1.52%	1.63%	2.08%
54	1.56%	1.65%	1.99%	1.91%	2.57%
55	1.35%	1.40%	1.64%	1.46%	2.12%
56	1.46%	1.49%	1.87%	1.77%	2.50%
57	1.29%	1.43%	1.79%	1.49%	2.24%
58	1.65%	1.70%	2.19%	1.96%	2.54%
59	1.54%	1.38%	1.85%	1.61%	1.98%
60	1.77%	1.64%	2.16%	1.78%	2.04%
61	1.81%	1.58%	1.92%	1.50%	1.68%
62	2.33%	2.00%	2.32%	1.68%	2.07%
63	2.06%	1.84%	1.95%	1.17%	1.56%
64	2.30%	2.26%	2.15%	1.26%	1.78%
65	2.11%	2.12%	1.99%	1.05%	1.68%
66	2.38%	2.68%	2.30%	1.11%	2.19%
67	2.05%	2.27%	1.94%	0.87%	1.86%
68	2.23%	2.40%	2.00%	1.06%	2.07%
69	2.08%	2.12%	1.76%	0.94%	1.81%
70	2.43%	2.42%	1.99%	1.25%	2.34%
71	2.01%	1.85%	1.64%	1.15%	1.77%
72	1.92%	1.92%	1.61%	1.36%	2.07%
73	1.61%	1.71%	1.40%	1.13%	1.78%
74	1.69%	1.69%	1.47%	1.41%	2.04%
75	1.35%	1.27%	1.12%	1.06%	1.32%

Table 7 (*Continued*)

Time	Mon	Weekdays	Fri	Sat	Sun
76	1.29%	1.26%	1.13%	1.19%	1.31%
77	1.17%	1.15%	1.03%	1.01%	1.00%
78	1.18%	1.15%	1.14%	1.10%	1.19%
79	0.83%	0.92%	0.89%	0.76%	0.81%
80	0.75%	0.84%	0.83%	0.77%	0.92%
81	0.64%	0.69%	0.64%	0.52%	0.82%
82	0.63%	0.66%	0.55%	0.46%	0.88%
83	0.57%	0.50%	0.37%	0.32%	0.64%
84	0.61%	0.52%	0.43%	0.34%	0.76%
85	0.56%	0.46%	0.38%	0.34%	0.62%
86	0.67%	0.57%	0.52%	0.40%	0.75%
87	0.52%	0.44%	0.46%	0.32%	0.58%
88	0.45%	0.44%	0.47%	0.41%	0.66%
89	0.35%	0.34%	0.39%	0.45%	0.54%
90	0.35%	0.35%	0.43%	0.51%	0.54%
91	0.19%	0.20%	0.27%	0.42%	0.36%
92	0.18%	0.18%	0.29%	0.43%	0.30%
93	0.13%	0.11%	0.22%	0.33%	0.12%
94	0.12%	0.11%	0.18%	0.24%	0.11%
95	0.04%	0.06%	0.08%	0.12%	0.08%

Table 8
Probability of travel (cumulative).

k	Km	Mon	Weekdays	Fri	Sat	Sun
0	<2	0.22917949	0.21110176	0.224643	0.21110176	0.20020176
1	<4	0.40713438	0.38936243	0.39172674	0.38936243	0.35961713
2	<6	0.50709795	0.51071555	0.50926986	0.51071555	0.47829158
3	<8	0.59882024	0.59218287	0.60156551	0.59218287	0.55480705
4	<10	0.65561197	0.65367563	0.66401779	0.65367563	0.61194712
5	<12.5	0.69032293	0.70196422	0.71391008	0.70196422	0.66313738
6	<15	0.75472976	0.7635326	0.76389908	0.7635326	0.7251566
7	<18.5	0.80461588	0.80302923	0.81311949	0.80302923	0.771473
8	<20	0.83900508	0.83542293	0.84329914	0.83542293	0.81502836
9	<25	0.88860334	0.88616926	0.90470785	0.88616926	0.86084511
10	<30	0.92303152	0.92040934	0.92839391	0.92040934	0.90145597
11	<35	0.94932388	0.94556082	0.94298257	0.94556082	0.91585863
12	<40	0.96128432	0.9583068	0.96231069	0.9583068	0.92247889
13	<45	0.96467203	0.96685348	0.96801052	0.96685348	0.92717667
14	<50	0.9763209	0.97537706	0.972619	0.97537706	0.93510342
15	<60	0.97966632	0.98305397	0.98302076	0.98305397	0.94832225
16	<70	0.98367105	0.98741263	0.9866826	0.98741263	0.95747725
17	<100	0.9908388	0.992556	0.99166396	0.992556	0.97390813
18	<150	0.99442675	0.99554262	0.99609742	0.99554262	0.98236626
19	<300	0.99876699	0.99794414	0.99809345	0.99794414	0.99491783
20	>300	1	1	1	1	1

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